HAS THE UKRAINE-RUSSIA WAR CHANGED THE PATTERNS OF COMMODITIES MARKET: THE CASE OF THE COMMODITY DOW JONES INDEX

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Abstract

The aim of this research is to examine whether seasonal patterns in the Commodity Dow Jone index changed after the start of the Ukranian war. The author is particularly focused on examining whether a February effect can be spotted after the onset of the war. The author also examines the pre- and after- war period to examine whether and how the overall patterns in the index changed as a result of the war.

Keywords: seasonality, Dow Jones Commodity Index, dummy variables, regression

JEL: F3, F6

Introduction

Seasonality can be defined as a recurring pattern of prices doing up or down at a particular month each year due to the events that happen occasionally through this month. Prices in this month significantly differ from prices during the year. When the month passes, they return to their normal levels. The seasonality is a short-term event that does not affect prices in the long-term. Seasonality can be monthly, weekly, daily.

Li and Zhang (Li et. al., 2018) do cross-sectional research of 21 advanced economies and 21 emerging markets. They conclude that in the emerging markets seasonality is not exhibited, while the advanced markets exhibit seasonality. The seasonal effects, however, are too diversified to be summarized in one group. An advanced market can have January, February effects, etc. It depends on the stock exchange. The research of Norvaisiene (Norvaisien et. al., 2015) examines the presences of Halloween effect and other monthly effects in Estonia (Nasdaq OMX Tallinn), Latvia (Nasdaq OMX Riga) and Litva (Nasdaq OMX Vilnius) in the period 2003-2014. As monthly effect they define the statistically significant changes in the prices of the indices during the respective month. The seasonality in October is called Halloween effect.

Their results show that the Estonian stock exchange has a January effect when the returns are higher than the rest of the months. Also, a Halloween effect is a present as in October the returns are significantly lower than in the rest of the year. In Latvia (Nasdaq OMX Riga), however, no monthly seasonality is present. Litva, on the other hand, exhibits January effect with higher returns. Similar monthly effects are present in August, when the returns are higher than in other months but lower than in January.

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In Lithuania seasonality is present dragging prices down. October has statistically significant monthly effect. The research (Norvaisien et. al., 2015) also shows that in all three Baltic countries the ‘winter’ period (November-April) exhibits higher returns that the ‘summer’ months (May- October).

Benjamin and Auer (Benjamin & Auer, 2014) test for daily seasonality in crude oil returns and volatilities. They find that on Mondays the crude oil returns are significantly lower than in the rest of the week, while the Monday volatilities are significantly higher than in the rest of the week. Qadan (Qadan M. & Idilbi-Bayaa, 2021) finds Monday and Friday effects in 30-day implied volatility of oil (OVX), gold (GVZ), silver (VXSLV) and the securities of companies from the energy sector (VXXLE). Mondays are associated with increased volatility, while Fridays with a decline. Zhang (Zhang et. al., 2017) finds Monday effect in SZC1, DOW, MERVAL, WIG20, FTSEMIB and STI index. Tuesday effect is present in SPX, SPXT. According to their research (Zhang et. al., 2017) Wednesday effect is present in MEXBOL, JCI, DAX, SMI, AS51, NKY and NZSE50FG. Thursday effects are present in SMEC, PX and PCOMP. Friday effect is present in IBOV, IPSA, RTSI$, XU100, SENSEX, FBMKLCI, IBEX, and HSI index.

Among the most common methods for seasonality detection are regression and time series analysis. Regression models include OLS dummy regression (Norvaisien et. al., 2015), where dummy variables for each month are included. Statistically significant coefficient means presence of a month effect (Norvaisien et. al., 2015). ARIMA is also often used to model seasonality (Zhao et. al., 2022), (Ning et. al., 2022), (Thakkar, 2020), (Bhandari et. al., 2022). ARIMA models are time-series models that can be of order p,d,q. The order of the model shows if differenced data have been used, how many periods were used for differencing, periods of seasonality and the order of integration of the model. ARIMA models, however, are not so flexible and in some cases, are hard to interpret. In recent years, machine learning (ML) has also been applied to model seasonality and predict stock market indices (Fischer & Krauss, 2018), (Patel et. al., 2015). Long-short-term memory models (LSTM) are a ML tool to handle seasonality (Cristofaro et. al., 2021), (Kobiela et. al., 2022), (Li & Li, 2023). They are more flexible than ARIMA models and allow handling long and short-term seasonality ((Kobiela et. al., 2022).

Another popular tool to tackle seasonality and make stock market predictions is the Python and R library – PROPHET (Quick Start | Prophet (facebook.github.io). This a novel library available in R and Python focused on time series predictions. Some authors have used it to build hybrid models combining the PROPHET library and ML algorithms (Guo et. al., 2021), (Borges, Nascimento, 2022). Ning et. al. (Ning et. al., 2022), makes comparison among ARIMA, LTSM and PROPHET to model oil prices. They come to the conclusion that ARIMA and LTSM predict better oil prices but the PROPHET models capture better fluctuations coming from seasonality. Ensafi (Ensafi et. al., 2022) showed that Convolutional Networks (CNN) and the Prophet models can be applied to predict the future behaviour of seasonal data. Other authors (Rick & Berton, 2022) argue that the Prophet models may require training n models, which may not be applicable to all kinds of data. This may make the Prophet models unfeasible for seasonality modelling in some cases.

Our research focuses on the dummy OLS regression (Norvaisien et. al., 2015) in order to test the Commodity Dow Jones Index for the presence of monthly effects before and after the Ukrainian war. Also, to examine if the index is characterized by monthly effects regardless of the Ukrainian war. Next sections comments on the methodology we use. Sections 3 and 4 comment on the results. Section 5 concludes.

Materials and Methods

Data Preparation

We use data about the Dow Jones Commodity Index taken by (https://www.spglobal.com/spdji/en/indices/commodities/dow-jones-commodity-index/#overview). Figure 1 presents the commodities that form the Commodity Dow Jones Index (https://www.spglobal.com/spdji/en/indices/commodities/dow-jones-commodity-index/#overview).

Commodity Contract Code	Commodity Name	Component
CL	WTI Crude Oil	Petroleum
HO	Heating Oil	
LCO	Brent Crude Oil	
RB	RBOB Gasoline	
LGO	Gasoil	
NG	Natural Gas	Natural Gas
W	Chicago Wheat	Wheat
KW	Kansas Wheat	
C	Corn	Corn
S	Soybeans	Soybeans
BO	Soybean Oil	
SM	Soybean Meal	
KC	Coffee	Coffee
SB	Sugar	Sugar
CC	Cocoa	Cocoa
CT	Cotton	Cotton
LC	Live Cattle	Cattle
FC	Feeder Cattle	
LH	Lean Hogs	Lean Hogs
MAL	Aluminum	Aluminum
MCU	LME Copper	Copper
HG	NA Copper	
MPB	Lead	Lead
MNI	Nickel	Nickel
MZN	Zinc	Zinc
SI	Silver	Silver
GC	Gold	Gold
PL	Platinum	Platinum

Source: https://www.spglobal.com/spdji/en/indices/commodities/dow-jones-commodity-index/#overview

Fig. 1. Components of the Commodity Dow Jones Index

Each component has attributed weight based on which its importance in the Commodity Dow Jones Index is ranked. The components and their weights are combined together using a formula described in (https://www.spglobal.com/spdji/en/indices/commodities/dow-jones-commodity-index/#overview) so that one index is formed. In this research we use the final index, which is the called the Commodity Dow Jones Index. This study does not include any other component of the Commodity Dow Jones Index.

The observations included in the research are on a daily basis. They are non-stationary. We convert the prices to returns using the natural logarithm to get stationary data. Then, a new dataset is produced using the ln return (R_{ti})of at the last day of each month. The tested period is January 2013- January 2023. The ln return (R_{ti}) marks the the return of the Commodity Dow Jones index at a given month and year.

We build three models in order to test the Commodity Dow Jones Index for seasonality.

Model 1: OLS Dummy Regression to check for seasonality regardless of the Ukraine war

We build a model similar to (Norvaisien et. al., 2015) that aims at checking if the Commodity Dow Jones Index is characterized by seasonality between January 2013 and January 2023. This model is not adjusted for the start of the Ukrainian war, nor any other shocks that may have occurred during the period. It checks for monthly effects that are present in the data regardless of any shocks.

Model 1 contains twelve dummy independent variables corresponding to each month in the year. The dependent y variable is the ln returns of the Commodity Dow Jones Index (R_{it}).

Model 1:

$$Rit = \beta_{1i}D_1 + \beta_{2i}D_2 + \beta_{3i}D_3 + \beta_{4i}D_4 + \beta_{5i}D_5 + \beta_{6i}D_6 + \beta_{7i}D_7 + \beta_{8i}D_8 + \\ +\beta_{9i}D_9 + \beta_{10}iD_{10} + \beta_{11i}D_{11} + \beta_{12i}D_{12} + \varepsilon \quad (1)$$

Where Rit is the monthly return of each index. D_1 through D_{12} are dummies for each month of the year. When D_1 equals 1, monthly returns increase in January. If it equals 0, monthly returns increase in any other calendar month of the year. The same applies for D_2 to D_{10}. The βis are coefficients estimated from the regression equation for each month. εt is the error term (Norvaisien et. al., 2015).

Models 2 and 3 check for seasonality in the returns of the Commodity Dow Jones Index before and after the war. They consist of one-year period before and after the war. February 2022 is used as a breaking point as this is the month when the war started. We took a period of one year before and after, as the after period has this length. Model 2 applies model 1 to the pre-war period (March 2021- February 2022).

Model 2: Seasonality checks one year before the Ukraine war (March 2021 – February 2022)

$$R_{it} = \beta_0 + \beta i February + \varepsilon_t \tag{2}$$

Where R_{it} is the monthly return of the Commodity Dow Jones Index. The term βi is a dummy variable that equals 1 for February returns and 0 for other months' returns. The coefficient βi designates the presence or lack of February effect. The term βi*February represents the difference between mean monthly returns during February over mean monthly returns of the other eleven months (Norvaisien et. al., 2015). The presence of February effect is then represented by a positive and statistically significant βiFebruary. The coefficient β_0 represents the mean monthly returns of the remaining eleven months. This model is applied to the period March 2021- February 2022.

Model 3 reapplies model 2 to the after-war period (February 2022 – January 2023).

Model 3: Seasonality checks one year after the Ukraine war

$$R_{it} = \beta_0 + \beta i February + \varepsilon_t \tag{3}$$

Where Rit is the monthly return of the Commodity Dow Jones Index. The term βi is a dummy variable that equals 1 for February returns and 0 for other months' returns. The coefficient βi designates the presence or lack of February effect. The term βi*February represents the difference between mean monthly returns during February over mean monthly returns of the other eleven months (Norvaisien et. al., 2015). The presence of February effect is then represented by a positive and statistically significant βiFebruary. The coefficient β_0 represents the mean monthly returns of the remaining eleven months.

As the war started in February 2022, it might be expected to cause disruptions in the Dow Jones Commodity Index that can have long-term effects. We build an additional model following (Girardin & Namin, 2019). Model 4 checks for statistically significant February effect.

Model 4: Additional check for February effect in the Commodity Dow Jones Index

We investigate whether the February mean returns are significantly higher than the returns of the other eleven months for the whole period. To do that, we evaluate a regression equation similar to (Norvaisien et. al., 2015):

$$R_{it} = \beta_0 + \beta i February + \varepsilon_t \tag{4}$$

Where Rit is the monthly return of the Commodity Dow Jones Index. The term βi is a dummy variable that equals 1 for February returns and 0 for other months' returns. The coefficient βi designates the presence or lack of February effect. The term βi*February represents the difference between mean monthly returns during February over mean monthly returns of the other eleven months (Norvaisien et. al., 2015). The presence of February effect is then represented by a positive and statistically significant βiFebruary. The coefficient β_0 represents the mean monthly returns o f the remaining eleven months.

The four models study at a greater depth the characteristics of the Dow Jones Commodity Index for the first time, allowing insights into its seasonal nature before, after and regardless of the Ukraine war. Therefore, we present a methodology to examine the spill-over effects of the Ukraine war on the commodity futures markets.

Next section comments on the results.

Results

Model 1: checks for monthly effects regardless of the Ukraine war

The first model includes the whole sample January 2013 – January 2023. It checks for monthly effects in the Commodity Dow Jones Index that are part of the natural cycle of the index. As the research focus is on the returns from the index, the expected results would be that returns in some months would be higher than the rest of the year, and lower in other months as many market indices exhibit these patters (Norvaisiene et. al., 2015), (Girardin & Namin, 2019).

Table 1. General Seasonal Model for the Commodity Dow Jones Index (January 2013 – January 2023)

	Coef	Std err	t	P>|t|	0.025	[0.975]
Intercept	0.01	0.05	0.31	0.76	-0.08	0.11
Jan	-0.02	0.05	-0.49	0.63	-0.12	0.07
Feb	0.00	0.05	0.06	0.95	-0.09	0.10
March	-0.04	0.05	-0.84	0.41	-0.14	0.06
April	-0.02	0.05	-0.40	0.69	-0.12	0.08
May	-0.01	0.05	-0.23	0.82	-0.11	0.09
June	0.00	0.05	0.04	0.97	-0.09	0.10
July	-0.02	0.05	-0.32	0.75	-0.11	0.08
August	-0.01	0.05	-0.12	0.91	-0.10	0.09
Sep	-0.02	0.05	-0.50	0.62	-0.12	0.07
Oct	-0.01	0.05	-0.17	0.87	-0.10	0.09
Nov	-0.02	0.05	-0.39	0.70	-0.12	0.08
Dec	-0.02	0.05	-0.42	0.68	-0.12	0.08

Source: author's calculations

Table 1 shows that seasonality is not typical for the Commodity Dow Jones Index. Unlike stock returns (Norvaisiene et. al., 2015), (Girardin & Namin, 2019), the returns from the Commodity Dow Jones Index do not tend to fluctuate with monthly events. The monthly p-values are statistically insignificant at the 1%, 5% and 10% significance levels. The month of February is not an exception. Therefore, monthly seasonality is not typical for the Commodity Dow Jones returns between January 2013 and January 2023. This does not mean that the returns do not exhibit cyclic patterns. Rather the finding means that repetitive patterns that occur each year at a particular month and affect the average returns are not typical for the Commodity Dow Jones index.

Model 1 shows that no monthly seasonality affects the returns from the Commodity Dow Jones Index for the past ten years. As the Ukraine war started in February 2022 and model 1 detected no seasonality in February, models 2 and 3 check if February 2022 can be considered a breaking point where the trend for no seasonality is reversed. Models 2 and 3 check if February 2022 has statistically significant effect on the monthly returns before and after the start of the Ukraine war and what the size of this effect is.

Model 2: Checks one year before the start of the Ukraine war

Table 2 shows the results from model 2, where the sample starts from March 2021 and ends in February 2022.

Table 2. Is February 2022 a Breaking Point in Returns Patterns?

	coef	Std err	t	P>|t|	[0.025	0.975]
Intercept	-0.027	0.013	-2.041	0.069	-0.057	0.002
February 2022	-0.042	0.046	-0.916	0.381	-0.144	0.06

Source: authors' calculations

As table 2 shows during the period March 2021 – February 2022, February does not affect the average Commodity Dow Jones Index returns (p-val. 0.381) as there is statistical insignificance. This result is not surprising as February 2022 is considered to an ending point of the previous period. A breaking point would be expected to change the future pattern rather than the past pattern.

Model 3: checks one year after the start of the Ukraine war

Table 3 shows the output from model 3, where the statistical significance of February 2022 is examined in the period February 2022 – January 2023.

Table 3. Output in the period February 2022 – January 2023

	coef	Std err	t	P>|t|	[0.025	0.975]
Intercept	0.0149	0.013	1.128	0.286	-0.015	0.044
Feb-22	-0.084	0.046	-1.831	0.097	-0.186	0.018

Source: authors' calculations

In the period February 2022 – January 2023, the month of February 2022 has statistically significant effects (p val – 0.97) on the Commodity Dow Jones Index returns.

This means that the patterns till February 2022 changed when the war started. February effect appeared in 2022 and affected the average returns of the Commodity Dow Jones Index negatively. One percent increase in the February 2022 returns would lead to a decrease of 8.4% in the average Commodity Dow Jones Index in the period February 2022 – January 2023. Therefore, the month of February 2022 can be considered a breaking point in the average Commodity Dow Jones Index returns. The question is whether this breaking point has only short-term effects or long-term effects that change the seasonality patters by inserting a February effect. Model 4 tries to answer this question.

Model 4: Additional check for February effect in the Commodity Dow Jones Index

Model 4 follows the same methodology as models 2 and 3 but it includes February 2023. This is done to check if the statistical significance from model 3 is kept when February 2023 is added in the model. If this is the case, then long-term change in seasonality patterns of the index can be proved. Model 4 contains the period between January 2013 and February 2023. Table 4 presents the results.

Table 4. Output from Model 4: Checks for February effect January 2013 – February 2023

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	0.00	0.00	-0.62	0.54	-0.01	0.01
February effect	0.02	0.02	1.32	0.19	-0.01	0.05

Source: authors' calculations

Table 4 confirms that when February 2023 is added to the ten-year dataset, the statistical significance of the February effect is not present. Therefore, when adding February 2023, there is no February effect as it was in model 1. Model 1 shows that for the ten-year period between January 2013 and January 2023, no monthly effects are present, incl. February effect. When February 2023 is added, the lack of February effect is confirmed by model 4. However, model 3 confirms the presence of February effect in the period February 2022 – January 2023.

Discussion

In this research we examine the question of the Ukraine war can affect seasonal patterns in the Commodity Dow Jones Index. Our findings can be summarized in several directions.

- First, February 2022 is a breaking point for the average Commodity Dow Jones returns. This is confirmed by models 1-3. Therefore, the Ukraine war can be considered an event that affected the Commodity Dow Jones Index statistically significant. This is another aspect of the war's consequences.
- Second, the Ukraine war is an event that affects the Commodity Dow Jones returns in the short term as the February effect is statistically significant only in the period February 2022 – January 2023 (model/ table 3).
- Third, in the period January 2013 – February 2023, there is no February effect. Therefore, the Ukraine war does not change the seasonality pattern of the Commodity Dow Jones returns in the long-term. The February effect in model 3 has a temporary short-term effects on the returns, so the February effect is not a change in the seasonality pattern as it is present only in one of the examined periods. The statistically significant February effect in table 3 is actually a shock to the Commodity Dow Jones returns.
- Lastly, table 1 shows that monthly effects are not typical for the Commodity Dow Jones between January 2013 and January 2023, so it is not surprising that the February effect could not be detected by the models. Ukraine war is a shock that does not change the returns long-term patterns.

Conclusion

This research proposes a deeper insight into the effects from the Ukraine war on the commodity markets through the Commodity Dow Jones Index. Unlike many authors citing the irreversible effects of the war on the crops, commodity markets, environment, economies and casualties, this research shows that the Commodity Dow Jones Index is more resilient than previously thought. The Ukraine war affects the index in the short term, and it does not introduce seasonality in the form of February effect. In fact, the statistically significant February 2022 effect is not present in the period January 2013 – February 2023, which means the effects of February 2022 start of the war have already been overcome. So, no change in the long-term seasonal patterns of the returns can be detected.

References

1. Benjamin R. Auer, Daily seasonality in crude oil returns and volatilities, Energy Economics, Volume 43, 2014, Pages 82-88, https://doi.org/10.1016/j.eneco.2014.02.005

2. Bhandari H., Rimal B., Pokhrel N., Dahal R., Khatri R., Predicting stock market index using LSTM, Machine Learning with Applications, Volume 9, 2022, https://doi.org/10.1016/j.mlwa.2022.100320

3. Borges D., Nascimento M., COVID-19 ICU demand forecasting: A two-stage Prophet-LSTM approach, Applied Soft Computing, Volume 125, 2022, https://doi.org/10.1016/j.asoc.2022.109181

4. Cristofaro L., Gil-Alana L., Chen Zh., Wanke P., Modelling stock market data in China: Crisis and Coronavirus, Finance Research Letters, Volume 41, 2021, https://doi.org/10.1016/j.frl.2020.101865.

5. Ensafi Y., Amin S., Zhang G., Shah B., Time-series forecasting of seasonal items sales using machine learning – A comparative analysis, International Journal of Information Management Data Insights, Volume 2, Issue 1, 2022, https://doi.org/10.1016/j.jjimei.2022.100058

6. Fischer T., Krauss C., Deep learning with long short-term memory networks for financial market predictions, European Journal of Operational Research, 270 (2) (2018), pp. 654 – 669.

7. Girardin E., Namin F., The January effect in the foreign exchange market: Evidence for seasonal equity carry trades, Economic Modelling, Volume 81, 2019, Pages 422-439, https://doi.org/10.1016/j.econmod.2019.07.021.

8. Guo L., Fang W., Zhao Q., Wang X., The hybrid PROPHET-SVR approach for forecasting product time series demand with seasonality, Computers & Industrial Engineering, Volume 161, 2021, https://doi.org/10.1016/j.cie.2021.107598

9. https://www.spglobal.com/spdji/en/indices/commodities/dow-jones-commodity-index/#overview Commodity Dow Jones Index, accessed January 2023

10. Kobiela D., Krefta D., Król W., Weichbroth P., ARIMA vs LSTM on NASDAQ stock exchange data, Procedia Computer Science, Volume 207, 2022, Pages 3836-3845, https://doi.org/10.1016/j.procs.2022.09.445.

11. Li F., Zhang H., Zheng D., Seasonality in the cross section of stock returns: Advanced markets versus emerging markets, Journal of Empirical Finance, Volume 49, 2018, Pages 263-281, https://doi.org/10.1016/j.jempfin.2018.11.001.

12. Li S.,Tian Zh., Li Y., Residual long short-term memory network with multi-source and multi-frequency information fusion: An application to China's stock market, Information Sciences, Volume 622, 2023, Pages 133 – 147, https://doi.org/10.1016/j.ins.2022.11.136

13. Ning Y., Kazemi H., Tahmasebi P., A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet, Comput. Geosci., 164 (2022).

14. Norvaisiene R., Stankeviciene J., Lakstutiene A., Seasonality in the Baltic Stock Markets, Procedia – Social and Behavioral Sciences, Volume 213, 2015, Pages 468-473, https://doi.org/10.1016/j.sbspro.2015.11.435

15. Patel J., Shah S., Thakkar P., Kotecha K., Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques, Expert Systems with Applications, 42 (1) (2015), pp. 259-268

16. PROPHET library, Quick Start | Prophet (facebook.github.io) , accessed March 2023.

17. Qadan M., Idilbi-Bayaa Y., The day-of-the-week-effect on the volatility of commodities, Resources Policy, Volume 71, 2021, https://doi.org/10.1016/j.resourpol.2020.101980.

18. Rick R., Berton L., Energy forecasting model based on CNN-LSTM-AE for many time series with unequal lengths, Engineering Applications of Artificial Intelligence, Volume 113, 2022, https://doi.org/10.1016/j.engappai.2022.104998.

19. Thakkar A., Chaudhari K., CREST: Cross-Reference to Exchange-based Stock Trend Prediction using Long Short-Term Memory, Procedia Computer Science, Volume 167, 2020, Pages 616-625, https://doi.org/10.1016/j.procs.2020.03.328

20. Zhang J., Lai Y., Lin J., The day-of-the-Week effects of stock markets in different countries, Finance Research Letters, Volume 20, 2017, Pages 47 – 62, https://doi.org/10.1016/j.frl.2016.09.006

21. Zhao L., Li Z., Qu ., Forecasting of Beijing PM2.5 with a hybrid ARIMA model based on integrated AIC and improved GS fixed-order methods and seasonal decomposition, Heliyon, Volume 8, Issue 12, 2022, https://doi.org/10.1016/j.heliyon.2022.e12239